Gaussian processes: The Bayes Rule

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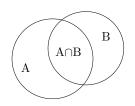
ECE, UNM

October, 2018

The Bayes Rule



Assume a universe of possible events Ω and two subsets $A, B \in \Omega$

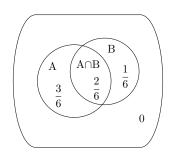


- P(A|B) = probability of Agiven that B occurred.
- Then B is our new universe.
- Bayes rule: $P(A|B) = \frac{P(A \cap B)}{P(B)}$

The intuitive interpretation is that since B occurred, then the rest of the universe disappears, as its probability is 0. The conditional probability is the fraction of areas between $A \cap B$ and B.

Bayes rule: an example





•
$$P(A) = \frac{3}{6} + \frac{2}{6} = \frac{5}{6}$$

•
$$P(B) = \frac{2}{6} + \frac{1}{6} = \frac{3}{6}$$

•
$$P(A \cup B) =$$

 $P(A) + P(B) - P(A \cap B) = 1$
Hence,
 $P(A \cap B) = \frac{5}{6} + \frac{3}{6} - 1 = \frac{2}{6}$

Then the probability of A given that B has occurred is

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{\frac{2}{6}}{\frac{3}{6}} = \frac{2}{3}$$

Corollary



• We can do inference over an event A|B known the distribution of B|A and the marginal distribution B.

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \Rightarrow \begin{cases} P(A \cap B) = P(A|B)P(B) \\ P(B \cap A) = P(B|A)P(A) \end{cases}$$

• Since $A \cap B = B \cap A$

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Bayes Rule on several conditional variables



• Now define the r.v. **w** and $y \cap x = y, x$ and compute $p(\mathbf{w}|y, x)$

$$p(\mathbf{w}|y, \mathbf{x}) = \frac{p(y, \mathbf{x}|\mathbf{w})p(\mathbf{w})}{p(y, \mathbf{x})}$$

$$p(y, \mathbf{x}) = p(y|\mathbf{x})p(\mathbf{x}), \qquad p(y, \mathbf{x}|\mathbf{w}) = p(y|\mathbf{x}, \mathbf{w})p(\mathbf{x})$$

• Then

$$p(\mathbf{w}|y, \mathbf{x}) = \frac{p(y|\mathbf{x}, \mathbf{w})p(\mathbf{x})p(\mathbf{w})}{p(y|\mathbf{x})p(\mathbf{x})} = \frac{p(y|\mathbf{x}, \mathbf{w})p(\mathbf{w})}{p(y|\mathbf{x})}$$

Finally:

$$p(\mathbf{w}|y,\mathbf{x}) \propto p(y|\mathbf{x},\mathbf{w})p(\mathbf{w})$$

Conclusion



• If w is a set of parameters of the estimator

$$y = \mathbf{w}^{\top} \mathbf{x} + \varepsilon$$

we call $p(\mathbf{w})$ the *prior* probability, and then $p(\mathbf{w}|y,\mathbf{x})$ is the posterior probability.

• Similarly, we can compute the output *likelihood* using the expressions of slide 5 as

$$p(y|\mathbf{x}, \mathbf{w}) = \frac{p(y, \mathbf{x}|\mathbf{w})}{p(\mathbf{x})}$$